## Init

```
In [1]:
```

```
try:
    import os
    import glob
    import sys
    import math
    from typing import List, Optional
    from functools import partial
    import itertools
    import copy
except Exception as e:
    print(e)
    print("Some of the libraries needed to run this script were not installed or were not loaded. Please install the libraries before proceeding.")
```

#### In [2]:

```
sys.path.append(os.environ['DEV_AUTOTS'])
sys.path.append(os.environ['CAPSTONE_PYTHON_SOURCE'])
folder = os.environ['CAPSTONE_DATA']
```

```
In [3]:
```

```
try:
    # Data Tables
    import pandas as pd
    import numpy as np
    # Plotting
    import matplotlib.pyplot as plt
    import plotly.offline as py
   from plotly.offline import plot
    py.init_notebook_mode(connected=True)
   # EDA and Feature Engineering
    from scipy.spatial.distance import euclidean, pdist, squareform
    import statsmodels.api as sm
    # Auto Time Series
    import auto_ts as AT
   # Optimizer
   from skopt import gp_minimize
   from skopt.space import Real, Integer
   from skopt.plots import plot_convergence
except Exception as e:
    print(e)
    print("Some of the libraries needed to run this script were not installed or were not loaded. Please install the libraries befo
re proceeding.")
```

Running Auto Timeseries version: 0.0.24

#### In [4]:

%load\_ext autoreload
%autoreload 2

```
from ETL.ETL import loadDataset, getTopProducts
   from similarity.similarity import mergeTopSimilar, loadSimilarity
   from charting.charting import surface3DChart
except Exception as e:
   print(e)
   print("Some of the libraries needed to run this script were not installed or were not loaded. Please install the libraries before proceeding.")
```

```
In [6]:
```

In [5]:

dataRaw= loadDataset(version=4)

# **Prep Data**

```
In [7]:
```

```
#Parameters
#ChainMaster = 'SPECS'
#ProdCat='SUP PREM WHISKEY'
TOP_PRODUCTS = 3 # How many products to consider in the category
TOP_SIMILAR = 3 # Get TOP_SIMILAR most similar products
LOG_TRANSFORM = True # Take log of 9L cases to smooth out peaks and valleys
ZERO\_ADDER = 0.1
RESAMPLE\_FREQ = 'M'
# Pricing changes every 4 weeks
if RESAMPLE_FREQ == 'M':
                           FORECAST_PERIOD = 1
if RESAMPLE_FREQ == 'W': FORECAST_PERIOD = 4
if RESAMPLE_FREQ == '2W': FORECAST_PERIOD = 2
# Seasonal Period
if RESAMPLE_FREQ == 'M':
                           SEASONAL_PERIOD = 12 # Yearly
if RESAMPLE_FREQ == 'W': SEASONAL_PERIOD = 13 # Quarterly (we can also take yearly = 52, but SARIMAX becomes too slow)
if RESAMPLE_FREQ == '2W': SEASONAL_PERIOD = 13 # This becomes problematic --> for quarterly, should we take 6 biweekly periods or
7 bi-weekly periods. Instead I just took half yearly period
print("="*50)
print("Parameters being used...")
print("="*50)
print(f"Resample Frequency = {RESAMPLE_FREQ}")
print(f"Forecast Period = {FORECAST_PERIOD}")
print(f"Seasonal Period = {SEASONAL_PERIOD}")
```

\_\_\_\_\_

Parameters being used...

Resample Frequency = M Forecast Period = 1

Seasonal Period = 12

## **Model Flow**

#### **Functions**



```
In [8]:
```

```
COL TIME = 'WeekDate'
COL_PREDS = ['9L Cases'] #Demand
COL_PRICE= ['Dollar Sales per 9L Case'] #Price
def modelsLoadData(ProductsList, dataRaw, ChainMaster):
    all_data = []
    if(ChainMaster!=''):
        dfSimilarity = loadSimilarity(version=4)
    else:
        dfSimilarity = loadSimilarity(version=4,allCustomers=True)
   for i, Product in enumerate(ProductsList):
        (dataModel,colExog,colEnc,colDec) = mergeTopSimilar(dataRaw, dfSimilarity
                                                             ,ChainMaster=ChainMaster
                                                             ,Product=Product
                                                             ,ProductsList=ProductsList
                                                             ,topn=TOP_SIMILAR
                                                             ,periodCol = COL_TIME
                                                             ,resampleFreq=RESAMPLE_FREQ
                                                             ,encodeCols=True)
        if i == 0: print(f"Decoder: {colDec}")
        print("\n\n")
        print("-"*50)
        print(f"Product: {colDec.get(str(i))}")
        print("-"*50)
        #colExog = colExog + colEndog
        print(f"Exogenous Price Columns: {colExog}")
        allCols=[COL_TIME]+COL_PREDS+ colExog
        data=dataModel[allCols]
        print(f"% of weeks without a purchase: {sum(data['9L Cases'] == 0)/data.shape[0]*100}")
        all_data.append(data)
   all_data_non_transformed = copy.deepcopy(all_data)
    if LOG TRANSFORM:
        print("Log Transforming")
        for i in np.arange(len(all_data)):
            all_data_non_transformed[i] = all_data[i].copy(deep=True)
            all_data[i][COL_PREDS] = np.log10(all_data[i][COL_PREDS] + ZERO_ADDER)
```

```
print(f"\tProduct: {colDec.get(str(i))}")
    return(all data,all data non transformed,colExog,colEnc,colDec)
def ModelsWhiteNoise(all data)
    ## WHITE NOISE TEST
   white noise all = []
    white noise df all = []
    #check if there are 12, 24, 48 data points
    for i, data in enumerate(all data):
        lags=[12,24,48]
        lags=[x for x in lags if x < data.shape[0]]</pre>
        white noise_df = sm.stats.acorr_ljungbox(data[COL_PREDS], lags=lags, return_df=True)
        white noise df all.append(white noise df)
        if any(white noise df['lb pvalue'] > 0.05):
            white noise = True
        else:
            white noise = False
        white noise all.append(white noise)
        print(white noise df)
        print(f"\nIs Data White Noise: {white_noise}")
    return(white noise all)
def ModelsTestTrain(all data,all data non transformed):
    all train = []
    all test = []
    all train non transformed = []
    all test non transformed = []
    for i, data in enumerate(all data):
        train = all data non transformed[i].iloc[:-FORECAST PERIOD]
        test = all data non transformed[i].iloc[-FORECAST PERIOD:]
        all train non transformed.append(train)
        all test non transformed.append(test)
        train = data.iloc[:-FORECAST PERIOD]
        test = data.iloc[-FORECAST PERIOD:]
        all train.append(train)
        all test.append(test)
        print(train.shape,test.shape)
    return(all train,all test,all train non transformed,all test non transformed)
def ModelsFit(all data,all train,all test,withSimilar,model type=['SARIMAX','ML','prophet','auto SARIMAX']):
    from joblib import Parallel, delayed
```

```
def modelsFun(i):
        train = all train[i]
        test = all test[i]
        import auto ts as AT
        if(withSimilar==False):
            train = train[train.columns[0:3]] #3rd col has the curr product price
        print(train.columns)
        automl model = AT.AutoTimeSeries(
            score type='rmse', forecast period=FORECAST PERIOD, # time interval='Week',
            non seasonal pdq=None, seasonality=True, seasonal period=SEASONAL PERIOD,
            model type=model type,
            verbose=0)
        #colP = COL PREDS[COL PREDS in train.columns]
        automl model.fit(train, COL TIME, COL PREDS, cv=10, sep=',') #cv=10
        return(automl model)
    args = np.arange(len(all data))
    all models = Parallel(n jobs=-1, verbose=1
                          #, backend="threading"
                           , backend="loky"
                         )(
             map(delayed(modelsFun), args))
   return(all models)
def get rmse(predictions, targets):
    return np.sqrt(((np.array(predictions) - np.array(targets)) ** 2).mean())
def modelNaive(all data,all train,all test,all train non transformed,season=12,windowLength=8):
   from sktime.forecasting.naive import NaiveForecaster
    import statistics
   from tscv import GapWalkForward # type: ignore
   all naives=pd.DataFrame(columns=['ID', 'Best Type', 'Best RMSE'])
   types=['last','seasonal last','mean']
    #add window code
    NFOLDS=5
   for i, data in enumerate(all data):
        yTrain = pd.Series(all train[i][COL PREDS[0]])
        yTest = pd.Series(all test[i][COL PREDS[0]])
        yTrain = yTrain.append(yTest) # merging as we are gong to do cv
        rmses=[]
        naive_models=[]
        for t in types:
```

```
#naive_forecaster = NaiveForecaster(strategy="last")
            cv = GapWalkForward(n splits=10, gap size=0, test size=FORECAST PERIOD)
            cvRmse=[]
            for fold number, (train, test) in enumerate(cv.split(yTrain)):
                cv train = yTrain.iloc[train]
                cv test = yTrain.iloc[test]
                naive forecaster = NaiveForecaster(strategy=t,sp=season,window length=windowLength)
                naive forecaster.fit(cv train)
                yPred = naive forecaster.predict(np.arange(len(cv test)))
                rmse=get rmse(yPred, cv test)
                cvRmse.append(rmse)
            #naive models.append(naive forecaster) #last forecaster
            rmses.append(np.mean(cvRmse))
        bestRmse = np.argmin(rmses)
        bestModel = NaiveForecaster(strategy=types[bestRmse],sp=season)
        yTrainNonTrasformed = pd.Series(all train non transformed[i][COL PREDS[0]])
        bestModel.fit(yTrainNonTrasformed)
        all naives=all naives.append(
            {'ID':i
             , 'Best Type': types[bestRmse]
             ,'Best RMSE': rmses[bestRmse]
             , 'Best Naive': bestModel
             ,'All Types': [types]
             ,'All RMSEs': [rmses]
             ,'All Naives':naive_models
            ,ignore index=True)
    print(all naives)
    return(all naives)
def centerLog(text,w,pre='\n',post=''):
    t=int((w-len(text))/2-1)
    return(pre+'='*t+' '+text+' '+'='*(w-len(text)-t-2)+post)
def printLog(main, subs, linesPre=2, linesPost=1):
    import datetime
    if(isinstance(subs,list)== False): subs=[subs]
    maxw=max([len(x) for x in [main] + subs])+10
    print("\n"*linesPre
          +"="*maxw+" ("+str(datetime.datetime.now())+")"
          +centerLog(main,maxw)
          +''.join([centerLog(x,maxw) for x in subs])
          +"\n"+"="*maxw
          +"\n"*linesPost
```

#### **Call Function**

```
In [9]:
```

```
def runModels(ProductsList,dataRaw,ChainMaster):
    printLog("GET DATA", ChainMaster)
    all data, all data non transformed, colExog, colEnc, colDec = modelsLoadData(ProductsList, dataRaw, ChainMaster)
    printLog("WHITE NOISE", ChainMaster)
    white noise = ModelsWhiteNoise(all data)
    printLog("TEST/TRAIN", ChainMaster)
    all train, all test, all train non transformed, all test non transformed = ModelsTestTrain(all data, all data non transformed)
    all stats = pd.DataFrame()
    all stats['Product'] = ProductsList
    all stats['Chain Master'] = ChainMaster
    all stats['White Noise'] = white noise
    printLog("NAIVE", ChainMaster)
    naive = modelNaive(all data,all train,all test,all data non transformed,season=4,windowLength=8)
    all stats['Naive Best Type'] = [naive.iloc[x]['Best Type'] for x in np.arange(len(all data))]
    all stats['Naive Best RMSE'] = [naive.iloc[x]['Best RMSE'] for x in np.arange(len(all data))]
    all stats['Naive Best Model'] = [naive.iloc[x]['Best Naive'] for x in np.arange(len(all data))]
    printLog("Multivar P0", ChainMaster)
    multivarP0 = ModelsFit(all data,all train,all test,withSimilar = False)
    all stats['P0 Best Model Name'] = [multivarP0[x].get leaderboard().iloc[0]['name'] for x in np.arange(len(all data)) ]
    all stats['P0 Best Model RMSE'] = [multivarP0[x].get leaderboard().iloc[0]['rmse'] for x in np.arange(len(all data)) ]
    all stats['P0 Best Model'] = multivarP0 #[multivarP0[x] for x in np.arange(len(all data)) ]
    printLog("Multivar P0+Sim", ChainMaster)
    multivarP0Sim = ModelsFit(all data,all train,all test,withSimilar = True )
    all stats['P0+Sim Best Model Name'] = [multivarP0Sim[x].get leaderboard().iloc[0]['name'] for x in np.arange(len(all data))]
    all stats['P0+Sim Best Model RMSE'] = [multivarP0Sim[x].get leaderboard().iloc[0]['rmse'] for x in np.arange(len(all data)) ]
    all stats['P0+Sim Best Model'] = multivarP0Sim #[multivarP0Sim[x] for x in np.arange(len(all data)) ]
    return(all stats)
```

## Loop

```
In [10]:
```

```
ChainMasters = [''] + dataRaw['Chain Master'].unique().tolist()
ProdCats = dataRaw['Category (CatMan)'].unique().tolist()
display(ChainMasters, ProdCats)

['', 'THE BARREL HOUSE', 'WESTERN BEV LIQ TX', 'SPECS']
['ECONOMY VODKA', 'SUP PREM WHISKEY']
```

## **Testing Models**

```
In [12]:
#getting train test
if False:
    ChainMaster=ChainMasters[0]
    ProductsList = getTopProducts(dataRaw, ChainMaster='WESTERN BEV LIQ TX', ProdCat='SUP PREM WHISKEY', topN=TOP_PRODUCTS, timeCol
='WeekDate')
    all_data,all_data_non_transformed,colExog,colEnc,colDec = modelsLoadData(ProductsList,dataRaw,ChainMaster)
    all_train, all_test,all_train_non_transformed,all_test_non_transformed = ModelsTestTrain(all_data,all_data_non_transformed)
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1.75L', '1': 'JACK DANIELS BLK WHSKY 750M', '2': 'JACK DANIELS BLK WHSKY 1
L'}
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['0', '2', '1']
% of weeks without a purchase: 1.1904761904761905
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
Exogenous Price Columns: ['1', '2', '0']
% of weeks without a purchase: 0.0
resampling to M
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['2', '0', '1']
% of weeks without a purchase: 0.0
Log Transforming
        Product: JACK DANIELS BLK WHSKY 1.75L
        Product: JACK DANIELS BLK WHSKY 750M
        Product: JACK DANIELS BLK WHSKY 1L
(83, 5) (1, 5)
```

(83, 5) (1, 5) (83, 5) (1, 5)

```
In [14]:
```

```
#Fitting model
if False:
   i=1
   withSimilar=False
   train = all train[i]
   test = all test[i]
   import auto ts as AT
   if(withSimilar==False):
        train = train[train.columns[0:3]] #3rd col has the curr product price
    print(train.columns)
   #model_type=['SARIMAX','ML','prophet','auto_SARIMAX']
   model type=['prophet']
   automl model = AT.AutoTimeSeries(
        score type='rmse', forecast period=FORECAST PERIOD, # time interval='Week',
        non seasonal pdq=None, seasonality=True, seasonal period=SEASONAL PERIOD,
        model type=model type,
        verbose=0)
    #colP = COL PREDS[COL PREDS in train.columns]
   automl model.fit(train, COL TIME, COL PREDS, cv=1, sep=',') #cv=10
```

#### In [15]:

```
#prediction
if False:
    display(automl_model.get_leaderboard())
    df=pd.DataFrame({'WeekDate': [pd.to_datetime('2019-12-31')],'0':[266.51]})
    prediction=automl_model.predict(X_exogen = df,forecast_period=1)
    print(prediction)
```

#### Run

#### In [16]:

```
full_stats=pd.DataFrame()
ProdCats = ['SUP PREM WHISKEY']
for ProdCat in ProdCats:
    for ChainMaster in ChainMasters:
        printLog("Running ",[ProdCat,ChainMaster])
        ProductsList = getTopProducts(dataRaw, ChainMaster=ChainMaster, ProdCat=ProdCat, topN=TOP_PRODUCTS, timeCol='WeekDate')
        all_stats=runModels(ProductsList,dataRaw,ChainMaster)
        all_stats['Product Category']=ProdCat
        display(all_stats)
        full_stats=full_stats.append(all_stats,ignore_index=True)

printLog("Completed","")
```

```
====== Running ======
==== SUP PREM WHISKEY ====
==== GET DATA ====
==============
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'JACK DANIELS BLK WHSKY 1.75L', '2': 'JACK DANIELS BLK WHSKY 750
M'}
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['0', '1', '2']
% of weeks without a purchase: 0.0
resampling to M
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['1', '0', '2']
% of weeks without a purchase: 1.1904761904761905
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
Exogenous Price Columns: ['2', '0', '1']
% of weeks without a purchase: 0.0
Log Transforming
      Product: JACK DANIELS BLK WHSKY 1L
      Product: JACK DANIELS BLK WHSKY 1.75L
```

Product: JACK DANIELS BLK WHSKY 750M

```
==== WHITE NOISE ====
lb_stat lb_pvalue
12 17.529696 0.130735
24 31.092108 0.151145
48 54.922995
          0.228882
Is Data White Noise: True
          lb_pvalue
    lb_stat
12 115.750529 4.333814e-19
24 214.169023 1.845834e-32
48 308.098428 1.176533e-39
Is Data White Noise: False
          lb_pvalue
    lb_stat
12 76.707883 1.745018e-11
24 131.122583 9.711501e-17
48 214.957410 5.416649e-23
Is Data White Noise: False
==== TEST/TRAIN ====
(83, 5) (1, 5)
(83, 5) (1, 5)
(83, 5) (1, 5)
==== NAIVE ====
==========
 ID Best Type Best RMSE All Naives \
0 0
                      mean
          0.043169
                      []
1 1
          0.324455
      last
                      2 2
      mean
          0.427990
```

```
1 [[0.3244545696539494, 0.4963154566538675, 0.34...
2 [[0.6704496090247218, 0.719929333484661, 0.427...
                 All Types
                                               Best Naive
0 [[last, seasonal last, mean]]
                         NaiveForecaster(sp=4, strategy='mean')
1 [[last, seasonal last, mean]]
                                      NaiveForecaster(sp=4)
2 [[last, seasonal_last, mean]] NaiveForecaster(sp=4, strategy='mean')
==== Multivar P0 ====
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 3.2min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
==== Multivar P0+Sim ====
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 3.1min finished
```

0 [[0.07143315389555474, 0.11332894033533458, 0....

|   | Product                                  | Chain<br>Master | White<br>Noise | Naive<br>Best<br>Type | Naive<br>Best<br>RMSE | Naive Best Model                          | P0 Best Model<br>Name | P0 Best<br>Model<br>RMSE | P0 Best Model   | P0+Sim Best<br>Model Name | P0+Sim<br>Best<br>Model<br>RMSE | I                   |
|---|--|-----------------|----------------|-----------------------|-----------------------|---|-----------------------|--------------------------|---|---------------------------|---------------------------------|---------------------|
| 0 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1L    |                 | True           | mean                  | 0.043169              | NaiveForecaster(sp=4,<br>strategy='mean') | SARIMAX               | 0.027899                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | SARIMAX                   | 0.021390                        | <aut< td=""></aut<> |
| 1 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1.75L |                 | False          | last                  | 0.324455              | NaiveForecaster(sp=4)                     | auto_SARIMAX          | 0.207729                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | auto_SARIMAX              | 0.240375                        | <aut< td=""></aut<> |
| 2 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>750M  |                 | False          | mean                  | 0.427990              | NaiveForecaster(sp=4,<br>strategy='mean') | SARIMAX               | 0.278152                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | auto_SARIMAX              | 0.312962                        | <aut< td=""></aut<> |

```
====== Running ======
==== SUP PREM WHISKEY ====
==== THE BARREL HOUSE ====
====== GET DATA ======
==== THE BARREL HOUSE ====
_____
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'GENTLEMAN JACK WHSKY 6PK 1L', '2': 'JACK DANIELS BLK WHSKY LSE 50
M'}
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['0', '1', '2']
% of weeks without a purchase: 45.23809523809524
resampling to M
Product: GENTLEMAN JACK WHSKY 6PK 1L
Exogenous Price Columns: ['1', '0', '2']
% of weeks without a purchase: 32.926829268292686
resampling to M
Product: JACK DANIELS BLK WHSKY LSE 50M
_____
Exogenous Price Columns: ['2', '0', '1']
% of weeks without a purchase: 10.714285714285714
Log Transforming
      Product: JACK DANIELS BLK WHSKY 1L
```

Product: GENTLEMAN JACK WHSKY 6PK 1L
Product: JACK DANIELS BLK WHSKY LSE 50M

```
===== WHITE NOISE ======
==== THE BARREL HOUSE ====
lb_stat lb_pvalue
12 24.932218
           0.015147
24 47.266936
           0.003107
48 103.010327
           0.000007
Is Data White Noise: False
    lb_stat lb_pvalue
12 8.641692 0.733192
24 19.315056 0.734985
48 47.523727 0.492264
Is Data White Noise: True
    lb_stat lb_pvalue
12 17.236016 0.140933
24 26.001364
          0.353096
48 67.920769 0.030671
Is Data White Noise: True
===== TEST/TRAIN ======
==== THE BARREL HOUSE ====
(83, 5) (1, 5)
(81, 5) (1, 5)
(83, 5) (1, 5)
====== NAIVE =======
==== THE BARREL HOUSE ====
ID Best Type Best RMSE All Naives \
0 0
                       mean
          1.149908
1 1
      mean
           0.611153
                       2 2
           0.252773
      mean
```

```
1 [[0.7042605406907361, 0.7703384907350979, 0.61...
2 [[0.4339763671614111, 0.5139045586878941, 0.25...
                  All Types
                                                 Best Naive
0 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
1 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
2 [[last, seasonal_last, mean]] NaiveForecaster(sp=4, strategy='mean')
===== Multivar P0 ======
==== THE BARREL HOUSE ====
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 2.9min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
==== Multivar P0+Sim =====
==== THE BARREL HOUSE ====
```

0 [[1.3378491195367055, 1.5550765479093094, 1.14...

[Parallel(n\_jobs=-1)]: Done 3 out of 3 | elapsed: 2.8min finished

|   | Product                                 | Chain<br>Master        | White<br>Noise | Naive<br>Best<br>Type | Naive<br>Best<br>RMSE | Naive Best Model                          | P0 Best Model<br>Name | P0 Best<br>Model<br>RMSE | P0 Best Model   | P0+Sim<br>Best<br>Model<br>Name | P0+Sim<br>Best<br>Model<br>RMSE | P(                      |
|---|---|------------------------|----------------|-----------------------|-----------------------|---|-----------------------|--------------------------|---|---------------------------------|---------------------------------|-------------------------|
| 0 | JACK<br>DANIELS<br>BLK WHSKY<br>1L      | THE<br>BARREL<br>HOUSE | False          | mean                  | 1.149908              | NaiveForecaster(sp=4,<br>strategy='mean') | auto_SARIMAX          | 0.712256                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CC</auto_ts.autotimeseries<br> | ML                              | 0.794521                        | <auto_< th=""></auto_<> |
| 1 | GENTLEMAN<br>JACK<br>WHSKY 6PK<br>1L    | THE<br>BARREL<br>HOUSE | True           | mean                  | 0.611153              | NaiveForecaster(sp=4,<br>strategy='mean') | ML                    | 0.191544                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CC</auto_ts.autotimeseries<br> | ML                              | 0.191544                        | <auto_< th=""></auto_<> |
| 2 | JACK<br>DANIELS<br>BLK WHSKY<br>LSE 50M | THE<br>BARREL<br>HOUSE | True           | mean                  | 0.252773              | NaiveForecaster(sp=4,<br>strategy='mean') | auto_SARIMAX          | 0.254032                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CC</auto_ts.autotimeseries<br> | ML                              | 0.267358                        | <auto_< th=""></auto_<> |

```
====== Running ======
==== SUP PREM WHISKEY =====
==== WESTERN BEV LIQ TX ====
====== GET DATA ======
==== WESTERN BEV LIQ TX ====
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1.75L', '1': 'JACK DANIELS BLK WHSKY 750M', '2': 'JACK DANIELS BLK WHSKY 1
L'}
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['0', '2', '1']
% of weeks without a purchase: 17.5
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
Exogenous Price Columns: ['1', '2', '0']
% of weeks without a purchase: 13.414634146341465
resampling to M
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['2', '1', '0']
% of weeks without a purchase: 0.0
Log Transforming
      Product: JACK DANIELS BLK WHSKY 1.75L
      Product: JACK DANIELS BLK WHSKY 750M
```

Product: JACK DANIELS BLK WHSKY 1L

```
====== WHITE NOISE ======
==== WESTERN BEV LIQ TX ====
_____
             lb_pvalue
    lb_stat
12 230.533574
          1.544168e-42
24 440.855949
          2.925831e-78
48 689.590939 1.731957e-114
Is Data White Noise: False
    lb_stat
            lb_pvalue
  77.815839 1.075181e-11
24 136.909527 8.579214e-18
48 201.387337 1.088599e-20
Is Data White Noise: False
    lb\_stat
           lb_pvalue
12 59.487140 2.799051e-08
24 75.433349 3.193517e-07
48 84.194254 9.632108e-04
Is Data White Noise: False
====== TEST/TRAIN ======
==== WESTERN BEV LIQ TX ====
(79, 5)(1, 5)
(81, 5) (1, 5)
(82, 5) (1, 5)
======= NAIVE =======
==== WESTERN BEV LIQ TX ====
ID Best Type Best RMSE All Naives \
0 0
       mean
          1.192388
                       1 1
      mean
          0.706690
                       2 2
           0.083096
                       mean
```

```
0 [[1.209792431243374, 1.8312196882995284, 1.192...
1 [[1.1305923379415006, 1.2624589917738127, 0.70...
2 [[0.12236276035592478, 0.0844886828891572, 0.0...
                  All Types
                                                  Best Naive
0 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
1 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
2 [[last, seasonal_last, mean]] NaiveForecaster(sp=4, strategy='mean')
===== Multivar P0 ======
==== WESTERN BEV LIQ TX ====
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 2.9min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
==== Multivar P0+Sim =====
==== WESTERN BEV LIQ TX ====
_____
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 3.0min finished
```

|   | Product                                  | Chain<br>Master          | White<br>Noise | Naive<br>Best<br>Type | Naive<br>Best<br>RMSE | Naive Best Model                          | P0 Best Model<br>Name | P0 Best<br>Model<br>RMSE | P0 Best Model   | P0+Sim Best<br>Model Name | P0+Sim<br>Best<br>Model<br>RMSE |   |
|---|--|--------------------------|----------------|-----------------------|-----------------------|---|-----------------------|--------------------------|---|---------------------------|---------------------------------|---|
| 0 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1.75L | WESTERN<br>BEV LIQ<br>TX | False          | mean                  | 1.192388              | NaiveForecaster(sp=4,<br>strategy='mean') | auto_SARIMAX          | 0.713414                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | SARIMAX                   | 0.651764                        | < |
| 1 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>750M  | WESTERN<br>BEV LIQ<br>TX | False          | mean                  | 0.706690              | NaiveForecaster(sp=4,<br>strategy='mean') | SARIMAX               | 0.578826                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | auto_SARIMAX              | 0.525101                        | < |
| 2 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1L    | WESTERN<br>BEV LIQ<br>TX | False          | mean                  | 0.083096              | NaiveForecaster(sp=4,<br>strategy='mean') | ML                    | 0.099956                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CA</auto_ts.autotimeseries<br> | ML                        | 0.099927                        | < |
|   |  |                          |                |                       |                       |   |                       |                          |   |                           |                                 |   |

```
====== Running ======
==== SUP PREM WHISKEY ====
====== SPECS =======
==== GET DATA ====
===== SPECS ======
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'JACK DANIELS BLK WHSKY 1.75L', '2': 'JACK DANIELS BLK WHSKY 750
M'}
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['0', '1', '2']
% of weeks without a purchase: 0.0
resampling to M
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['1', '0', '2']
% of weeks without a purchase: 8.333333333333333
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
Exogenous Price Columns: ['2', '0', '1']
% of weeks without a purchase: 2.380952380952381
Log Transforming
      Product: JACK DANIELS BLK WHSKY 1L
```

Product: JACK DANIELS BLK WHSKY 1.75L Product: JACK DANIELS BLK WHSKY 750M

```
==== WHITE NOISE ====
===== SPECS ======
lb_stat lb_pvalue
12 15.190957 0.231159
24 26.538512
           0.326419
           0.445959
48 48.667832
Is Data White Noise: True
    lb_stat lb_pvalue
12 29.265420 0.003598
24 41.411630 0.015005
48 54.239869 0.248702
Is Data White Noise: True
    lb_stat lb_pvalue
12 26.913026 0.007953
24 38.221972
           0.032900
48 54.395929
           0.244080
Is Data White Noise: True
==== TEST/TRAIN ====
===== SPECS ======
==============
(83, 5) (1, 5)
(83, 5) (1, 5)
(83, 5) (1, 5)
==== NAIVE ====
==== SPECS ====
==========
 ID Best Type Best RMSE All Naives \
0 0
                         mean
           0.060885
                         []
1 1
       mean
            0.159196
                         2 2
            0.276661
       mean
```

```
0 [[0.10753730489356994, 0.13940924570407018, 0....
1 [[0.1620938777280673, 0.22871564971857916, 0.1...
2 [[0.4671173585435577, 0.5316177371745061, 0.27...
                  All Types
                                                  Best Naive
0 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
1 [[last, seasonal last, mean]]
                           NaiveForecaster(sp=4, strategy='mean')
2 [[last, seasonal_last, mean]] NaiveForecaster(sp=4, strategy='mean')
==== Multivar P0 ====
===== SPECS ======
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 2.3min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
==== Multivar P0+Sim ====
====== SPECS ======
[Parallel(n_jobs=-1)]: Done 3 out of 3 | elapsed: 3.2min finished
```

|   | Product                                  | Chain<br>Master | White<br>Noise | Naive<br>Best<br>Type | Naive<br>Best<br>RMSE | Naive Best Model                          | P0 Best Model<br>Name | P0 Best<br>Model<br>RMSE | P0 Best Model   | P0+Sim<br>Best<br>Model<br>Name | P0+Sim<br>Best<br>Model<br>RMSE | P0+S                             |
|---|--|-----------------|----------------|-----------------------|-----------------------|---|-----------------------|--------------------------|---|---------------------------------|---------------------------------|----------------------------------|
| 0 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1L    | SPECS           | True           | mean                  | 0.060885              | NaiveForecaster(sp=4,<br>strategy='mean') | SARIMAX               | 0.037469                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CF</auto_ts.autotimeseries<br> | SARIMAX                         | 0.033760                        | <auto_ts. <="" td=""></auto_ts.> |
| 1 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>1.75L | SPECS           | True           | mean                  | 0.159196              | NaiveForecaster(sp=4,<br>strategy='mean') | SARIMAX               | 0.119452                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | SARIMAX                         | 0.137105                        | <auto_ts.<i>I 0&gt;</auto_ts.<i> |
| 2 | JACK<br>DANIELS<br>BLK<br>WHSKY<br>750M  | SPECS           | True           | mean                  | 0.276661              | NaiveForecaster(sp=4,<br>strategy='mean') | auto_SARIMAX          | 0.237800                 | <auto_ts.autotimeseries<br>object at<br/>0x00000228CD</auto_ts.autotimeseries<br> | SARIMAX                         | 0.249464                        | <auto_ts.<i>I Ox</auto_ts.<i>    |
| 4 |  |                 |                |                       |                       |   |                       |                          |   |                                 |                                 |                                  |

# **Print out**

#### In [15]:

full\_stats[full\_stats.columns.difference(['P0 Best Model','P0+Sim Best Model','Naive Best Model'],sort=False)]

### Out[15]:

|    | Product                           | Chain Master          | White<br>Noise | Naive<br>Best<br>Type | Naive<br>Best<br>RMSE | P0 Best Model<br>Name | P0 Best<br>Model<br>RMSE | P0+Sim Best<br>Model Name | P0+Sim Best<br>Model RMSE | Product<br>Category |
|----|-----------------------------------|-----------------------|----------------|-----------------------|-----------------------|-----------------------|--------------------------|---------------------------|---------------------------|---------------------|
| 0  | JACK DANIELS BLK<br>WHSKY 1L      |                       | True           | mean                  | 0.043169              | SARIMAX               | 0.027899                 | ML                        | 0.030409                  | SUP PREM<br>WHISKEY |
| 1  | JACK DANIELS BLK<br>WHSKY 1.75L   |                       | False          | last                  | 0.324455              | auto_SARIMAX          | 0.207729                 | auto_SARIMAX              | 0.186881                  | SUP PREM<br>WHISKEY |
| 2  | JACK DANIELS BLK<br>WHSKY 750M    |                       | False          | mean                  | 0.427990              | SARIMAX               | 0.278152                 | SARIMAX                   | 0.258481                  | SUP PREM<br>WHISKEY |
| 3  | JACK DANIELS BLK<br>WHSKY 1L      | THE BARREL<br>HOUSE   | False          | mean                  | 1.149908              | auto_SARIMAX          | 0.712256                 | ML                        | 0.798112                  | SUP PREM<br>WHISKEY |
| 4  | GENTLEMAN JACK<br>WHSKY 6PK 1L    | THE BARREL<br>HOUSE   | True           | mean                  | 0.611153              | ML                    | 0.191544                 | ML                        | 0.191544                  | SUP PREM<br>WHISKEY |
| 5  | JACK DANIELS BLK<br>WHSKY LSE 50M | THE BARREL<br>HOUSE   | True           | mean                  | 0.252773              | auto_SARIMAX          | 0.254032                 | auto_SARIMAX              | 0.261385                  | SUP PREM<br>WHISKEY |
| 6  | JACK DANIELS BLK<br>WHSKY 1.75L   | WESTERN<br>BEV LIQ TX | False          | mean                  | 1.192388              | auto_SARIMAX          | 0.713414                 | Prophet                   | 0.739690                  | SUP PREM<br>WHISKEY |
| 7  | JACK DANIELS BLK<br>WHSKY 750M    | WESTERN<br>BEV LIQ TX | False          | mean                  | 0.706690              | SARIMAX               | 0.578826                 | auto_SARIMAX              | 0.514482                  | SUP PREM<br>WHISKEY |
| 8  | JACK DANIELS BLK<br>WHSKY 1L      | WESTERN<br>BEV LIQ TX | False          | mean                  | 0.083096              | ML                    | 0.099956                 | auto_SARIMAX              | 0.089549                  | SUP PREM<br>WHISKEY |
| 9  | JACK DANIELS BLK<br>WHSKY 1L      | SPECS                 | True           | mean                  | 0.060885              | SARIMAX               | 0.037469                 | ML                        | 0.039430                  | SUP PREM<br>WHISKEY |
| 10 | JACK DANIELS BLK<br>WHSKY 1.75L   | SPECS                 | True           | mean                  | 0.159196              | SARIMAX               | 0.119452                 | SARIMAX                   | 0.137262                  | SUP PREM<br>WHISKEY |
| 11 | JACK DANIELS BLK<br>WHSKY 750M    | SPECS                 | True           | mean                  | 0.276661              | auto_SARIMAX          | 0.237800                 | SARIMAX                   | 0.233663                  | SUP PREM<br>WHISKEY |

# Saving

```
In [16]:
```

#full\_stats.to\_pickle('all\_Models\_stats.pkl')

# **Optimizer**

# **Functions**

**Optimizer Functions** 

```
In [17]:
```

```
def complex_objective(x: List
                      , ts_index_name: str
                      , ts_index: List
                      , all_models: List
                      , all data: List
                      , mask: Optional[List[bool]] = None
                      , verbose: int = 0
                      , return_individual: bool = False
                      , logT = False
                      , P0_only = False
                      #argument for P0 only
                      ):
    :param x A list of product pricing for which the revenue has to be computed
    :type x List
    :param mask: If the customer is not going to purchase a product in a period, we can choose to omit it from the revenue calculat
ion in the optimizer.
                 Default = None (considers all products in revenue calculation)
    :type mask Optional[List[bool]]
    param ts_index The index to use for the test data. This is needed for some models (such as ML) that use this to create feature:
    :type ts_index List
    :param return_individual If True, this returns the individual revenue values as well
                             Used mainly when this function is called standalone. Set of False for optimization
    :type return_individual bool
    :param verbose Level of verbosity (Default: 0). This is set to 1 or 2 (mainly for debug purposes)
    :type verbose int
    if verbose >0: print ("### Prediction Function ###")
   # Create test data from input
   index = [str(i) for i in np.arange(len(x))]
   x_df = pd.DataFrame(x, index = index)
    x_df = x_df.T
   # Set index (important for some models)
   x_df.index = ts_index
   x_df.index.name = ts_index_name
   # If mask is not provided, use all
    if mask is None:
        mask = [False for item in x]
```

```
if verbose >= 2:
    print(x df.info())
    print(x df.columns)
total revenue = 0
revenue = []
for i in np.arange(len(all data)):
    if verbose >= 1:
       print("\n" + "-"*50)
       print(f"Product Index: {i}")
    if not mask[i]:
        if P0 only: columns = [all data[i].columns[-(TOP SIMILAR+1)]]
       else: columns = all data[i].columns[-(TOP SIMILAR+1):].values #columns[-(TOP SIMILAR+2)] for the PO only type
        if verbose >= 2:
           print(f"All Columns in Test Data: {columns}")
           print('i:',i)
           print(x df[columns])
           print("----")
        test data = x df[columns]
       prediction = all models[i].predict(X exogen = test data, forecast period=1) #change this back when Nikhil fixes the auto
       if verbose >= 2: print(f"Prediction Type: {type(prediction)}")
       if verbose >= 1: print(f"Demand Prediction (transformed): {prediction}")
        # If model was created with log transformation
        if logT:
           prediction = 10**prediction
           if verbose >= 1:
               print("\nDemand Prediction (Original)")
               print(prediction)
        product revenue = prediction * x[i]
        # TODO: Clamping - Fix later (this gives an error with pandas. We need to pluck it out as a value)
       # product revenue = max(product revenue, 0) # Clamp at min value of 0 for predictions that are negative
       if verbose >= 1: print(f"Product Revenue: ${round(product revenue)}")
        if isinstance(product revenue, pd.Series):
           product revenue = product revenue.iloc[0]
        revenue.append(product revenue)
        # total revenue = total revenue + product revenue
    else:
```

TS

```
if verbose >= 1: print("This product's revenue was not included since it was not ordered by the customer in this period.")

product_revenue = 0
    revenue.append(product_revenue)

if verbose >= 1: print("-"*50 + "\n")

total_revenue = sum(revenue)

if verbose >= 1:
    print("\n\n" + "="*50)
    print(f"Total Revenue: ${round(total_revenue)}")
    print("="*50 + "\n\n")
    print("## Prediction Function END ###")

if return_individual is True: return -total_revenue

return -total_revenue
```

#### **Core Functions**

```
In [18]:
```

```
def opt get mask(all data,all test):
    # Did the customer actually want to but products in that period?
    # Only include the revenue in the objective if they actually ordered it
    # This model is not trying to predict if they would purchase a product when they were not going to purchase it earlier.
    # That requires a lot of human psychology and may not be captured in the model
    INCLUDE_MASKING = True
    mask: List[bool] = []
    for index in np.arange(len(all data)):
        if INCLUDE MASKING:
            if all_test[index].iloc[0]['9L Cases'] == 0:
                mask.append(True)
            else:
                mask.append(False)
        else:
            mask.append(False)
    print(f"Mask: {mask}")
    return(mask)
def opt_get_space(all_data,MARGIN=0.0):
    MARGIN = 0.0 # How much to go over or under the min and max price respectively during the search for optimial revenue
    space = []
    for index in np.arange(len(all_data)):
        #min val = all data[index][str(index)].min()
        min val = np.percentile(all_data[index][str(index)], 10)
        #max val = all data[index][str(index)].max()
        max_val = np.percentile(all_data[index][str(index)], 90)
        min_limit = min_val*(1-MARGIN)
        max limit = max val*(1+MARGIN)
        space.append(Real(low=min_limit, high=max_limit, prior='uniform'))
    return(space)
def opt_get_func(all_data,all_models,complex_objective,test_index_name,test_index,mask,verbose=0,P0_only=False):
    # create a new function with mask
    masked complex objective = partial(complex_objective, ts_index_name=test_index_name, ts_index=test_index, mask=mask, logT=LOG_T
RANSFORM, verbose=verbose
                                      ,all_models=all_models,all_data=all_data,P0_only=P0_only)
    if P0 only:
        print(f"Revenue P0: ${-round(complex_objective([266.51, 195.06, 205.3], ts_index_name=test_index_name, ts_index=test_index,
mask=mask,logT=LOG TRANSFORM,verbose=verbose,all models=all models,all data=all data,P0 only=True))}")
    else:
```

```
print(f"Revenue without masking: ${-round(complex objective([266.51, 195.06, 205.3], ts index name=test index name, ts index
x=test index, logT=LOG TRANSFORM, verbose=verbose, all models=all models, all data=all data))}")
        print(f"Revenue with masking: ${-round(masked complex objective([266.51, 195.06, 205.3], verbose=verbose, all models=all mode
ls,all data=all data))}")
    return(masked complex objective)
def opt get data(all data,all test non transformed):
    total test data revenue = 0
    for index in np.arange(len(all data)):
        product price = all test non transformed[index].iloc[0][str(index)]
        product demand = all test non transformed[index].iloc[0]['9L Cases']
        product revenue = product price * product demand
        print(f"Product {index} Price 9L Case: ${round(product price,2)} Revenue: ${round(product revenue)}")
        total test data revenue = total test data revenue + product revenue
    print(f"Total Revenue: ${round(total test data revenue)}")
    return(total test data revenue)
def opt naive(all models,all test non transformed):
    #uses test price and predict demand based on naive model
    product price=[]
    product demand=[]
    product revenue=[]
    for index in np.arange(len(all models)):
        product price.append(all test non transformed[index].iloc[0][str(index)])
        product demand.append(all models[index].predict([0]).tolist()[0])
        product revenue.append(product price[index] * product demand[index])
    total revenue = sum(product revenue)
    return(product price,product demand,product revenue,total revenue)
def opt get chart(all data,all models,space,ChainMaster,ProdCat,test index,test index name,verbose=1,STEPS=5,displayPlots=True,save
Path = '3d charts/'):
    math.ceil(space[0].low)
    math.floor(space[0].high)
    xs = np.arange(math.ceil(space[0].low), math.floor(space[0].high), step=5)
    ys = np.arange(math.ceil(space[1].low), math.floor(space[1].high), step=5)
    allp = [np.arange(math.ceil(space[i].low), math.floor(space[i].high), step=STEPS) for i in np.arange(len(all data))]
    if verbose >= 1:
        print("-"*100)
        print(f"Price intervals for product 0: {allp[0]}")
        print(f"Price intervals for product 1: {allp[1]}")
        print(f"Price intervals for product 2: {allp[2]}")
        print("-"*100, "\n")
    filenames=[]
    for i in np.arange(len(all data)):
        print("\n\n")
```

```
mask plot = [False if i == j else True for j in np.arange(len(all data))]
        if verbose >= 1:
            print(f"Product {i} --> Mask: {mask plot}")
        columns = all data[i].columns[-(TOP SIMILAR+1):].values
        if verbose >= 1:
            print(f"Products used in Model: {columns}")
        masked complex objective plot = partial(complex objective, ts index name=test index name, ts index=test index, mask=mask pl
ot, logT=LOG TRANSFORM, verbose=0
                                               ,all models=all models,all data=all data)
        finalx = []
        finaly = []
        finalrev = []
        xs = allp[int(columns[0])] # Main Product Price is in xs
        ys = allp[int(columns[1])] # Exogenous Product Price in in ys
        if verbose >= 1:
            print(f"Price intervals used for X-axis (product {int(columns[0])}): {xs}")
            print(f"Price intervals used for Y-axis (product {int(columns[1])}): {ys}")
        for x, y in itertools.product(xs, ys):
            price list = [0, 0, 0]
            # Fix price for product 0
            if int(columns[0]) == 0: # If the main product is product 0
                price list[0] = x
            elif int(columns[1]) == 0: # If exogenous product is product 0
                price list[0] = y
            else:
                price list[0] = 0
            # Fix price for product 1
            if int(columns[0]) == 1: # If the main product is product 1
                price list[1] = x
            elif int(columns[1]) == 1: # If exogenous product is product 1
                price list[1] = y
            else:
                price list[1] = 0
            # Fix price for product 2
            if int(columns[0]) == 2: # If the main product is product 2
                price list[2] = x
            elif int(columns[1]) == 2: # If exogenous product is product 2
                price list[2] = y
            else:
```

```
price list[2] = 0
            rev = -masked_complex_objective_plot(price_list)
            finalx.append(x)
            finaly.append(y)
            finalrev.append(rev)
        fig = surface3DChart(
            x=finalx, y=finaly, z=finalrev,
            title= 'Product ' + columns[0] + ' Revenue',
            xTitle= 'Product ' + columns[0] + ' Price',
            yTitle= 'Product ' + columns[1] + ' Price',
            width=1200,
            height=800
            )
        filename = "".join(ChainMaster.split()) + " " + "".join(ProdCat.split()) + " Top" + str(TOP PRODUCTS) + " Sim" + str(TOP SI
MILAR) + \
            "_Log" + str(LOG_TRANSFORM) + "_Add" + str(ZERO_ADDER) + \
            "Prod" + str(i) + "_Resample" + str(RESAMPLE_FREQ) + "_f" + str(FORECAST_PERIOD) + "_s" + str(SEASONAL_PERIOD) + ".htm
1"
        filenameFull = os.path.join(savePath,filename)
        if verbose >=1: print(filenameFull)
        filenames.append(filenameFull)
        py.plot(fig, filename = filenameFull,auto open=displayPlots)
   return(filenames)
```

# **Call Function**

```
In [24]:
```

```
def runOptimizer(ProductsList,dataRaw,ChainMaster,modelsStats,verbose=0):
    opt stats = pd.DataFrame()
   numProducts = len(ProductsList)
   opt stats['Chain Master'] = [ChainMaster] * numProducts
   opt_stats['Product'] = ProductsList
    printLog("GET DATA", ChainMaster)
    all data,all data non transformed,colExog,colEnc,colDec = modelsLoadData(ProductsList,dataRaw,ChainMaster)
    printLog("TEST/TRAIN", ChainMaster)
   all_train, all_test, all_train_non_transformed, all_test_non_transformed = ModelsTestTrain(all_data,all_data_non_transformed)
   opt_stats['Actual Demand'] = [all_test_non_transformed[x]['9L Cases'].values[0] for x in np.arange(3)]
    opt_stats['Actual Price'] = [all_test_non_transformed[x].iloc[0][str(x)] for x in np.arange(3)]
   opt_stats['Actual Revenue'] = [opt_stats['Actual Demand'][x] * opt_stats['Actual Price'][x] for x in np.arange(numProducts)]
   opt_stats['Actual Chain Master Revenue'] = [sum(opt_stats['Actual Revenue'])] *numProducts
    printLog("NAIVE FORECAST", ChainMaster)
    all models = modelsStats['Naive Best Model']
   naive_price, naive_demand, naive_revenue , naive_total_revenue = opt_naive(all_models,all_test_non_transformed) #uses test price
and predict demand based on naive
   opt_stats['Naive Prices'] = naive_price
   opt_stats['Naive Demand'] = naive_demand
   opt stats['Naive Revenue'] = naive revenue
   opt_stats['Naive Chain Master Revenue'] = [naive_total_revenue] * numProducts
    printLog("MASK", ChainMaster)
   mask = opt_get_mask(all_data,all_test)
    opt stats['mask'] = mask
    printLog("SPACE", ChainMaster)
    space = opt_get_space(all_data)
    opt stats['space'] = space
    printLog("Test Index", ChainMaster)
    test index name = 'WeekDate'
   test_index = all_test_non_transformed[0][test_index_name].values
   opt_stats['test_index'] = [test_index] * numProducts# for i in ProductsList]
    ############
    ## P0 Only ##
   if True:
        printLog("GET FUNCTION PO", ChainMaster)
        all models = modelsStats['P0 Best Model']
        masked_complex_objective = opt_get_func(all_data,all_models,complex_objective,test_index_name,test_index,mask=mask,verbose=
```

```
verbose,P0 only=True)
        opt stats['masked complex objective'] = masked complex objective
        printLog("OPTIMIZING PO", ChainMaster)
        res = gp_minimize(masked_complex_objective,
                          space,
                          acq func="EI",
                          n calls=200,
                          n random starts=20,
                          random_state=42)
        opt stats['res'] = [res] * numProducts # for i in ProductsList]
        ## GET OUTPUT DATA ##
        printLog("OUTPUT PO", ChainMaster)
        opt stats['P0 Optimal Price'] = [round(price, 2) for price in res.x]
        opt_stats['P0 Chain Master Revenue'] = round(-res.fun)
        __,all_revenues = masked_complex_objective(res.x, return individual=True)
        opt_stats['P0 Demand'] = (np.array(all_revenues) / np.array(opt_stats['P0 Optimal Price'])).tolist()
        opt stats['P0 Revenue'] = all revenues
        total test data revenue = opt get data(all data,all test non transformed)
        opt stats['total test data revenue P0'] = total test data revenue
    ############
    ## P0+Sim ##
    printLog("GET FUNCTION PO+Sim", ChainMaster)
   all models = modelsStats['P0+Sim Best Model']
   masked complex objective = opt get func(all data,all models,complex objective,test index name,test index,mask,verbose=verbose,P
0 only=False)
    opt stats['masked complex objective'] = masked complex objective
    printLog("OPTIMIZING P0+Sim", ChainMaster)
    res = gp minimize(masked complex objective,
                      space,
                      acq func="EI",
                      n calls=200,
                      n random starts=20,
                      random state=42
    opt stats['res'] = [res] * numProducts # for i in ProductsList]
    ## GET OUTPUT DATA ##
    printLog("OUTPUT P0+Sim", ChainMaster)
    opt stats['P0+Sim Optimal Price'] = [round(price, 2) for price in res.x]
    opt stats['P0+Sim Chain Master Revenue'] = round(-res.fun)
     ,all_revenues = masked_complex_objective(res.x, return_individual=True)
```

# Loop

In [25]:

```
#reading models data
#full_stats = pd.read_pickle('all_Models_stats.pkl')
#check mask.. change the iteration to 10 random and 20 full
```

```
In [26]:
```

```
ChainMasters = [''] + dataRaw['Chain Master'].unique().tolist()
ProdCats = dataRaw['Category (CatMan)'].unique().tolist()
display(ChainMasters, ProdCats)
```

```
['', 'THE BARREL HOUSE', 'WESTERN BEV LIQ TX', 'SPECS']
['ECONOMY VODKA', 'SUP PREM WHISKEY']
```

# **Testing Models**

#### In [27]:

```
## testing Models Prediction
if False:
    ChainMaster = ChainMasters[2]#Western
    ProdCat = 'SUP PREM WHISKEY'
    modelsStats = full_stats[(full_stats['Chain Master']==ChainMaster) & (full_stats['Product Category']==ProdCat)].reset_index()
    display(modelsStats)
    #display(modelsStats)
    model = modelsStats['P0 Best Model'][1]
    #df=pd.DataFrame({'WeekDate': [pd.to_datetime('2019-12-31')],'0':[266.51],'1':[195.06],'2':[195.06]})
    df=pd.DataFrame({'WeekDate': [pd.to_datetime('2019-12-31')],'1':[266.51]})
    prediction=model.predict(X_exogen = df,forecast_period=1)
    print(prediction)
```

#### In [28]:

```
full_opt_stats=pd.DataFrame()
ProdCats = ['SUP PREM WHISKEY']
for ProdCat in ProdCats:
    for ChainMaster in ChainMasters:
        modelsStats = full_stats[(full_stats['Chain Master']==ChainMaster) & (full_stats['Product Category']==ProdCat)].reset_index
()

    printLog("Get Top Similar Products",[ProdCat,ChainMaster])
    ProductsList = getTopProducts(dataRaw, ChainMaster=ChainMaster, ProdCat=ProdCat, topN=TOP_PRODUCTS, timeCol='WeekDate')

    printLog("Running Optimizer",[ProdCat,ChainMaster])
    opt_stats=runOptimizer(ProductsList,dataRaw,ChainMaster,modelsStats,verbose=0)

#dispLay(opt_stats)
    full_opt_stats=full_opt_stats.append(opt_stats,ignore_index=True)

printLog("Completed","")
```

```
==== Get Top Similar Products ====
====== SUP PREM WHISKEY ======
==== Running Optimizer ====
==== SUP PREM WHISKEY =====
==== GET DATA ====
==============
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'JACK DANIELS BLK WHSKY 1.75L', '2': 'JACK DANIELS BLK WHSKY 750
M'}
Product: JACK DANIELS BLK WHSKY 1L
-----
Exogenous Price Columns: ['0', '1']
% of weeks without a purchase: 0.0
resampling to M
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['1', '0']
% of weeks without a purchase: 1.1904761904761905
resampling to M
```

```
Exogenous Price Columns: ['2', '0']
% of weeks without a purchase: 0.0
Log Transforming
    Product: JACK DANIELS BLK WHSKY 1L
    Product: JACK DANIELS BLK WHSKY 1.75L
    Product: JACK DANIELS BLK WHSKY 750M
==== TEST/TRAIN ====
(83, 4) (1, 4)
(83, 4) (1, 4)
(83, 4) (1, 4)
==== NAIVE FORECAST ====
==== MASK ====
======
==========
Mask: [False, False, False]
==== SPACE ====
====== =====
_____
==== Test Index ====
```

Product: JACK DANIELS BLK WHSKY 750M

```
==== GET FUNCTION P0 ====
Revenue P0: $272192.0
==== OPTIMIZING P0 ====
==== OUTPUT P0 ====
Product 0 Price 9L Case: $229.81 Revenue: $135402.0
Product 1 Price 9L Case: $185.65 Revenue: $72331.0
Product 2 Price 9L Case: $222.36 Revenue: $50031.0
Total Revenue: $257765.0
==== GET FUNCTION PO+Sim ====
Revenue without masking: $214111.0
Revenue with masking: $214111.0
==== OPTIMIZING P0+Sim ====
==== OUTPUT P0+Sim ====
```

```
Product 1 Price 9L Case: $185.65 Revenue: $72331.0
Product 2 Price 9L Case: $222.36 Revenue: $50031.0
Total Revenue: $257765.0
==== COMPLETED ====
-----
==== Get Top Similar Products ====
====== SUP PREM WHISKEY ======
====== THE BARREL HOUSE ======
==== Running Optimizer ====
==== SUP PREM WHISKEY =====
==== THE BARREL HOUSE =====
===== GET DATA ======
==== THE BARREL HOUSE ====
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'GENTLEMAN JACK WHSKY 6PK 1L', '2': 'JACK DANIELS BLK WHSKY LSE 50
M'}
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['0', '1']
% of weeks without a purchase: 45.23809523809524
resampling to M
```

Product 0 Price 9L Case: \$229.81 Revenue: \$135402.0

```
Product: GENTLEMAN JACK WHSKY 6PK 1L
Exogenous Price Columns: ['1', '0']
% of weeks without a purchase: 32.926829268292686
resampling to M
Product: JACK DANIELS BLK WHSKY LSE 50M
Exogenous Price Columns: ['2', '0']
% of weeks without a purchase: 10.714285714285714
Log Transforming
     Product: JACK DANIELS BLK WHSKY 1L
     Product: GENTLEMAN JACK WHSKY 6PK 1L
     Product: JACK DANIELS BLK WHSKY LSE 50M
===== TEST/TRAIN ======
==== THE BARREL HOUSE ====
(83, 4) (1, 4)
(81, 4) (1, 4)
(83, 4) (1, 4)
==== NAIVE FORECAST =====
==== THE BARREL HOUSE ====
====== MASK =======
==== THE BARREL HOUSE ====
Mask: [False, False, False]
====== SPACE =======
```

```
==== THE BARREL HOUSE ====
===== Test Index =====
==== THE BARREL HOUSE ====
==== GET FUNCTION P0 =====
==== THE BARREL HOUSE ====
Revenue P0: $557.0
==== OPTIMIZING P0 =====
==== THE BARREL HOUSE ====
===== OUTPUT P0 ======
==== THE BARREL HOUSE ====
Product 0 Price 9L Case: $239.01 Revenue: $636.0
Product 1 Price 9L Case: $286.87 Revenue: $1345.0
Product 2 Price 9L Case: $268.66 Revenue: $360.0
Total Revenue: $2341.0
==== GET FUNCTION P0+Sim ====
==== THE BARREL HOUSE =====
Revenue without masking: $867.0
Revenue with masking: $867.0
```

```
==== OPTIMIZING P0+Sim ====
==== THE BARREL HOUSE =====
==== OUTPUT P0+Sim =====
==== THE BARREL HOUSE ====
Product 0 Price 9L Case: $239.01 Revenue: $636.0
Product 1 Price 9L Case: $286.87 Revenue: $1345.0
Product 2 Price 9L Case: $268.66 Revenue: $360.0
Total Revenue: $2341.0
===== COMPLETED ======
==== THE BARREL HOUSE ====
==== Get Top Similar Products ====
====== SUP PREM WHISKEY ======
====== WESTERN BEV LIQ TX ======
==== Running Optimizer =====
==== SUP PREM WHISKEY =====
==== WESTERN BEV LIQ TX ====
====== GET DATA ======
==== WESTERN BEV LIQ TX ====
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1.75L', '1': 'JACK DANIELS BLK WHSKY 750M', '2': 'JACK DANIELS BLK WHSKY 1
L'}
```

```
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['0', '2']
% of weeks without a purchase: 17.5
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
   -----
Exogenous Price Columns: ['1', '2']
% of weeks without a purchase: 13.414634146341465
resampling to M
Product: JACK DANIELS BLK WHSKY 1L
    -----
Exogenous Price Columns: ['2', '1']
% of weeks without a purchase: 0.0
Log Transforming
      Product: JACK DANIELS BLK WHSKY 1.75L
      Product: JACK DANIELS BLK WHSKY 750M
      Product: JACK DANIELS BLK WHSKY 1L
====== TEST/TRAIN ======
==== WESTERN BEV LIQ TX ====
(79, 4) (1, 4)
(81, 4) (1, 4)
(82, 4) (1, 4)
===== NAIVE FORECAST =====
==== WESTERN BEV LIQ TX ====
```

\_\_\_\_\_

```
======= MASK =======
==== WESTERN BEV LIQ TX ====
Mask: [False, False, False]
======= SPACE =======
==== WESTERN BEV LIQ TX ====
====== Test Index ======
==== WESTERN BEV LIO TX ====
==== GET FUNCTION P0 =====
==== WESTERN BEV LIQ TX ====
Revenue P0: $60042276.0
===== OPTIMIZING P0 ======
==== WESTERN BEV LIQ TX ====
====== OUTPUT P0 ======
==== WESTERN BEV LIQ TX ====
Product 0 Price 9L Case: $185.59 Revenue: $39085.0
Product 1 Price 9L Case: $222.36 Revenue: $34466.0
```

Product 2 Price 9L Case: \$230.79 Revenue: \$25476.0

Total Revenue: \$99027.0

```
==== GET FUNCTION PO+Sim ====
==== WESTERN BEV LIO TX =====
Building Forecast dataframe. Forecast Period = 1
Revenue without masking: $375471.0
Building Forecast dataframe. Forecast Period = 1
Revenue with masking: $375471.0
==== OPTIMIZING P0+Sim =====
==== WESTERN BEV LIO TX ====
Building Forecast dataframe. Forecast Period = 1
```

```
Building Forecast dataframe. Forecast Period = 1
```

```
Building Forecast dataframe. Forecast Period = 1
```

```
Building Forecast dataframe. Forecast Period = 1
```

```
Building Forecast dataframe. Forecast Period = 1
===== OUTPUT P0+Sim ======
==== WESTERN BEV LIQ TX ====
_____
Building Forecast dataframe. Forecast Period = 1
Product 0 Price 9L Case: $185.59 Revenue: $39085.0
Product 1 Price 9L Case: $222.36 Revenue: $34466.0
Product 2 Price 9L Case: $230.79 Revenue: $25476.0
Total Revenue: $99027.0
==== WESTERN BEV LIO TX ====
```

==== Get Top Similar Products ====

```
====== SUP PREM WHISKEY ======
======= SPECS ========
==== Running Optimizer ====
==== SUP PREM WHISKEY =====
======= SPECS =======
_____
==== GET DATA ====
==== SPECS =====
=============
resampling to M
Decoder: {'0': 'JACK DANIELS BLK WHSKY 1L', '1': 'JACK DANIELS BLK WHSKY 1.75L', '2': 'JACK DANIELS BLK WHSKY 750
M'}
Product: JACK DANIELS BLK WHSKY 1L
Exogenous Price Columns: ['0', '1']
% of weeks without a purchase: 0.0
resampling to M
 ______
Product: JACK DANIELS BLK WHSKY 1.75L
Exogenous Price Columns: ['1', '0']
% of weeks without a purchase: 8.333333333333333
resampling to M
Product: JACK DANIELS BLK WHSKY 750M
```

Exogenous Price Columns: ['2', '0']
% of weeks without a purchase: 2.380952380952381

```
Log Transforming
    Product: JACK DANIELS BLK WHSKY 1L
    Product: JACK DANIELS BLK WHSKY 1.75L
    Product: JACK DANIELS BLK WHSKY 750M
==== TEST/TRAIN ====
===== SPECS ======
============
(83, 4) (1, 4)
(83, 4) (1, 4)
(83, 4) (1, 4)
==== NAIVE FORECAST ====
====== SPECS ======
==== MASK =====
==== SPECS ====
===========
Mask: [False, False, False]
==== SPACE ====
==== SPECS ====
==========
==== Test Index ====
===== SPECS ======
==== GET FUNCTION P0 ====
```

```
Revenue P0: $189945.0
==== OPTIMIZING P0 ====
====== SPECS ======
==== OUTPUT P0 ====
===== SPECS =====
Product 0 Price 9L Case: $229.53 Revenue: $109290.0
Product 1 Price 9L Case: $185.59 Revenue: $32788.0
Product 2 Price 9L Case: $222.36 Revenue: $15343.0
Total Revenue: $157421.0
==== GET FUNCTION PO+Sim ====
======= SPECS =======
Revenue without masking: $90148.0
Revenue with masking: $90148.0
==== OPTIMIZING PO+Sim ====
==== OUTPUT P0+Sim ====
====== SPECS ======
Product 0 Price 9L Case: $229.53 Revenue: $109290.0
Product 1 Price 9L Case: $185.59 Revenue: $32788.0
Product 2 Price 9L Case: $222.36 Revenue: $15343.0
```

Total Revenue: \$157421.0

# **Print out**

#### In [29]:

|   | Chain<br>Master          | Product                                 | Actual<br>Price | Actual<br>Demand | Actual<br>Revenue | Actual<br>Chain<br>Master<br>Revenue | Naive<br>Prices | Naive<br>Demand | Naive<br>Revenue | Naive Chain<br>Master<br>Revenue | P0<br>Optimal<br>Price | P0<br>Demand |
|---|--------------------------|---|-----------------|------------------|-------------------|--------------------------------------|-----------------|-----------------|------------------|----------------------------------|------------------------|--------------|
| 0 |                          | JACK<br>DANIELS<br>BLK WHSKY<br>1L      | 229.811232      | 589.19           | 135402.48         | 257764.62                            | 229.811232      | 292.610723      | 67245.230832     | 90321.715676                     | 227.71                 | 296.250933   |
| 1 |                          | JACK<br>DANIELS<br>BLK WHSKY<br>1.75L   | 185.650112      | 389.61           | 72331.14          | 257764.62                            | 185.650112      | 40.950000       | 7602.372072      | 90321.715676                     | 184.44                 | 184.916178   |
| 2 |                          | JACK<br>DANIELS<br>BLK WHSKY<br>750M    | 222.360000      | 225.00           | 50031.00          | 257764.62                            | 222.360000      | 69.590361       | 15474.112771     | 90321.715676                     | 223.78                 | 169.864344   |
| 3 | THE<br>BARREL<br>HOUSE   | JACK<br>DANIELS<br>BLK WHSKY<br>1L      | 239.007519      | 2.66             | 635.76            | 2341.20                              | 239.007519      | 9.200506        | 2198.990116      | 2900.866248                      | 222.56                 | 225.475606   |
| 4 | THE<br>BARREL<br>HOUSE   | GENTLEMAN<br>JACK<br>WHSKY 6PK<br>1L    | 286.874200      | 4.69             | 1345.44           | 2341.20                              | 286.874200      | 1.169049        | 335.370107       | 2900.866248                      | 295.95                 | 1.484805     |
| 5 | THE<br>BARREL<br>HOUSE   | JACK<br>DANIELS<br>BLK WHSKY<br>LSE 50M | 268.656716      | 1.34             | 360.00            | 2341.20                              | 268.656716      | 1.364217        | 366.506024       | 2900.866248                      | 267.99                 | 1.272531     |
| 6 | WESTERN<br>BEV LIQ<br>TX | JACK<br>DANIELS<br>BLK WHSKY<br>1.75L   | 185.589744      | 210.60           | 39085.20          | 99027.48                             | 185.589744      | 110.560063      | 20518.813797     | 44989.509807                     | 191.28                 | 166.023589   |
| 7 | WESTERN<br>BEV LIQ<br>TX | JACK<br>DANIELS<br>BLK WHSKY<br>750M    | 222.360000      | 155.00           | 34465.80          | 99027.48                             | 222.360000      | 41.041148       | 9125.909702      | 44989.509807                     | 217.61                 | 165.010479   |
| 8 | WESTERN<br>BEV LIQ<br>TX | JACK<br>DANIELS<br>BLK WHSKY<br>1L      | 230.786122      | 110.39           | 25476.48          | 99027.48                             | 230.786122      | 66.489207       | 15344.786307     | 44989.509807                     | 224.24                 | 58.682795    |
| 9 | SPECS                    | JACK<br>DANIELS<br>BLK WHSKY<br>1L      | 229.533835      | 476.14           | 109290.24         | 157421.22                            | 229.533835      | 217.722084      | 49974.584892     | 63726.848507                     | 226.50                 | 222.317808   |

|    | Chain<br>Master | Product                               | Actual<br>Price | Actual<br>Demand | Actual<br>Revenue | Actual<br>Chain<br>Master<br>Revenue | Naive<br>Prices | Naive<br>Demand | Naive<br>Revenue | Naive Chain<br>Master<br>Revenue | P0<br>Optimal<br>Price | P0<br>Demand |
|----|-----------------|---------------------------------------|-----------------|------------------|-------------------|--------------------------------------|-----------------|-----------------|------------------|----------------------------------|------------------------|--------------|
| 10 | SPECS           | JACK<br>DANIELS<br>BLK WHSKY<br>1.75L | 185.589744      | 176.67           | 32788.14          | 157421.22                            | 185.589744      | 44.962771       | 8344.629157      | 63726.848507                     | 184.04                 | 49.283717    |
| 11 | SPECS           | JACK<br>DANIELS<br>BLK WHSKY<br>750M  | 222.360000      | 69.00            | 15342.84          | 157421.22                            | 222.360000      | 24.319277       | 5407.634458      | 63726.848507                     | 205.54                 | 112.562539   |
| 4  |                 |                                       |                 |                  |                   |                                      |                 |                 |                  |                                  |                        | •            |

## In [30]:

## Out[30]:

|    | Chain Master          | Product                           | Actual<br>Price | Actual<br>Demand | Actual<br>Revenue | Actual Chain<br>Master Revenue | Naive<br>Prices | Naive<br>Demand | Naive<br>Revenue | Naive Chain<br>Master<br>Revenue |
|----|-----------------------|-----------------------------------|-----------------|------------------|-------------------|--------------------------------|-----------------|-----------------|------------------|----------------------------------|
| 0  |                       | JACK DANIELS BLK<br>WHSKY 1L      | 229.811232      | 589.19           | 135402.48         | 257764.62                      | 229.811232      | 292.610723      | 67245.230832     | 90321.715676                     |
| 1  |                       | JACK DANIELS BLK<br>WHSKY 1.75L   | 185.650112      | 389.61           | 72331.14          | 257764.62                      | 185.650112      | 40.950000       | 7602.372072      | 90321.715676                     |
| 2  |                       | JACK DANIELS BLK<br>WHSKY 750M    | 222.360000      | 225.00           | 50031.00          | 257764.62                      | 222.360000      | 69.590361       | 15474.112771     | 90321.715676                     |
| 3  | THE BARREL<br>HOUSE   | JACK DANIELS BLK<br>WHSKY 1L      | 239.007519      | 2.66             | 635.76            | 2341.20                        | 239.007519      | 9.200506        | 2198.990116      | 2900.866248                      |
| 4  | THE BARREL<br>HOUSE   | GENTLEMAN JACK<br>WHSKY 6PK 1L    | 286.874200      | 4.69             | 1345.44           | 2341.20                        | 286.874200      | 1.169049        | 335.370107       | 2900.866248                      |
| 5  | THE BARREL<br>HOUSE   | JACK DANIELS BLK<br>WHSKY LSE 50M | 268.656716      | 1.34             | 360.00            | 2341.20                        | 268.656716      | 1.364217        | 366.506024       | 2900.866248                      |
| 6  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 1.75L   | 185.589744      | 210.60           | 39085.20          | 99027.48                       | 185.589744      | 110.560063      | 20518.813797     | 44989.509807                     |
| 7  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 750M    | 222.360000      | 155.00           | 34465.80          | 99027.48                       | 222.360000      | 41.041148       | 9125.909702      | 44989.509807                     |
| 8  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 1L      | 230.786122      | 110.39           | 25476.48          | 99027.48                       | 230.786122      | 66.489207       | 15344.786307     | 44989.509807                     |
| 9  | SPECS                 | JACK DANIELS BLK<br>WHSKY 1L      | 229.533835      | 476.14           | 109290.24         | 157421.22                      | 229.533835      | 217.722084      | 49974.584892     | 63726.848507                     |
| 10 | SPECS                 | JACK DANIELS BLK<br>WHSKY 1.75L   | 185.589744      | 176.67           | 32788.14          | 157421.22                      | 185.589744      | 44.962771       | 8344.629157      | 63726.848507                     |
| 11 | SPECS                 | JACK DANIELS BLK<br>WHSKY 750M    | 222.360000      | 69.00            | 15342.84          | 157421.22                      | 222.360000      | 24.319277       | 5407.634458      | 63726.848507                     |

## In [31]:

# Out[31]:

|    | Chain Master          | Product                           | P0<br>Optimal<br>Price | P0<br>Demand | P0 Revenue   | P0 Chain<br>Master<br>Revenue | P0+Sim<br>Optimal<br>Price | P0+Sim<br>Demand | P0+Sim<br>Revenue | P0+Sim<br>Chain<br>Master<br>Revenue |
|----|-----------------------|-----------------------------------|------------------------|--------------|--------------|-------------------------------|----------------------------|------------------|-------------------|--------------------------------------|
| 0  |                       | JACK DANIELS BLK<br>WHSKY 1L      | 227.71                 | 296.250933   | 67459.300020 | 139577.0                      | 228.75                     | 208.300856       | 47648.820791      | 121133.0                             |
| 1  |                       | JACK DANIELS BLK<br>WHSKY 1.75L   | 184.44                 | 184.916178   | 34105.939952 | 139577.0                      | 169.93                     | 244.776787       | 41594.919344      | 121133.0                             |
| 2  |                       | JACK DANIELS BLK<br>WHSKY 750M    | 223.78                 | 169.864344   | 38012.242857 | 139577.0                      | 224.13                     | 142.278525       | 31888.885832      | 121133.0                             |
| 3  | THE BARREL<br>HOUSE   | JACK DANIELS BLK<br>WHSKY 1L      | 222.56                 | 225.475606   | 50181.850796 | 50962.0                       | 234.28                     | 1.199191         | 280.946564        | 1059.0                               |
| 4  | THE BARREL<br>HOUSE   | GENTLEMAN JACK<br>WHSKY 6PK 1L    | 295.95                 | 1.484805     | 439.428095   | 50962.0                       | 296.93                     | 1.484796         | 440.880342        | 1059.0                               |
| 5  | THE BARREL<br>HOUSE   | JACK DANIELS BLK<br>WHSKY LSE 50M | 267.99                 | 1.272531     | 341.025472   | 50962.0                       | 268.45                     | 1.255788         | 337.116310        | 1059.0                               |
| 6  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 1.75L   | 191.28                 | 166.023589   | 31756.992175 | 80824.0                       | 185.37                     | 552.712908       | 102456.391798     | 123698.0                             |
| 7  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 750M    | 217.61                 | 165.010479   | 35907.930285 | 80824.0                       | 217.87                     | 26.238294        | 5716.537039       | 123698.0                             |
| 8  | WESTERN<br>BEV LIQ TX | JACK DANIELS BLK<br>WHSKY 1L      | 224.24                 | 58.682795    | 13159.029857 | 80824.0                       | 214.47                     | 72.389591        | 15525.395586      | 123698.0                             |
| 9  | SPECS                 | JACK DANIELS BLK<br>WHSKY 1L      | 226.50                 | 222.317808   | 50354.983567 | 82561.0                       | 229.22                     | 246.414206       | 56483.064251      | 66969.0                              |
| 10 | SPECS                 | JACK DANIELS BLK<br>WHSKY 1.75L   | 184.04                 | 49.283717    | 9070.175337  | 82561.0                       | 181.38                     | 31.088421        | 5638.817880       | 66969.0                              |
| 11 | SPECS                 | JACK DANIELS BLK<br>WHSKY 750M    | 205.54                 | 112.562539   | 23136.104353 | 82561.0                       | 209.29                     | 23.160338        | 4847.227201       | 66969.0                              |

# In [ ]: